

Predicting state of charge of lead-acid batteries for hybrid electric vehicles by extended Kalman filter

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Abstract

This paper describes and introduces a new nonlinear predictor and a novel battery model for estimating the state of charge (SoC) of lead-acid batteries for hybrid electric vehicles (HEV). Many problems occur for a traditional SoC indicator, such as offset, drift and long term state divergence, therefore this paper proposes a technique based on the extended Kalman filter (EKF) in order to overcome these problems. The underlying dynamic behavior of each cell is modeled using two capacitors (bulk and surface) and three resistors (terminal, surface and end). The SoC is determined from the voltage present on the bulk capacitor. In this new model, the value of the surface capacitor is constant, whereas the value of the bulk capacitor is not. Although the structure of the model, with two constant capacitors, has been previously reported for lithium-ion cells, this model can also be valid and reliable for lead-acid cells when used in conjunction with an EKF to estimate SoC (with a little variation). Measurements using real-time road data are used to compare the performance of conventional internal resistance (R_{int}) based methods for estimating SoC with those predicted from the proposed state estimation schemes. The results show that the proposed method is superior to the more traditional techniques, with accuracy in estimating the SoC within 3%.

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1. Introduction

Peak power demands of hybrid electric vehicles are subject to large dynamic transients in current and power. An example is the Manhattan driving cycle that shows road data collected from a Toyota Prius HEV, where the required maximum charge and discharge current are 10 A and 25 A, respectively, when subjected to a series of vehicle driving tests [1]. The satisfaction of such operating conditions needs a management system that has accurate knowledge of the peak power buffer's state of charge to facilitate safe and efficient operation.

Various electric equivalent circuit models have been applied to lead-acid batteries to determine the SoC. How-

ever, accurate description of the complex nonlinear electrochemical processes that occur during power transfer to/from the battery are dynamically difficult. These processes include the flow of ions, amount of stored charge, ability to deliver instantaneous power, the effects of temperature, internal pressure etc. [2,3]. A variety of techniques have been proposed to measure or monitor the SoC of a cell or battery, each having its own characteristics, as reviewed by Piller et al. [4]. Coulomb counting or current integration is the most commonly used technique. It requires dynamic measurement of the cell/battery current, and its time integral is used to provide a direct indication of the SoC [5]. However, because of the reliance on integration, errors in terminal measurements due to noise, resolution and rounding are cumulative, and large SoC errors can result. A reset or recalibration action is, therefore, required at regular intervals in all electric vehicles (EVs). This may be performed during a full charge or conditioning discharge,

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but it is not appropriate for standard HEV operation where full SoC is rarely achieved. Other factors that ultimately influence the accuracy of SoC estimates and cause additional complications to the traditional integration based techniques are the variation of cell capacity with discharge rate, temperature and Coulombic efficiency losses [2,6].

When considering flooded lead-acid cells, the specific gravity of the electrolyte is known to be a good measure of SoC [6]. However, the estimation of SoC gets complicated when using valve regulated lead-acid (VRLA) cells due to the nominal amount of electrolyte being immobilized in the glass fiber separator mat or gel. Nevertheless, since the open circuit terminal voltage of a VRLA battery varies almost linearly over the majority of the battery's SoC (Fig. 1) [2,3,7], it has been used in many SoC estimators. Note that this curve has been individually obtained from a case study battery in room temperature and constant discharge rate. To be an effective method, however, corrections must be made for temperature and electrolyte concentration gradients (concentration polarization) formed during high rate charges and discharges (long settling times may be required to allow such concentration gradients to disperse prior to making an open circuit voltage reading [3]).

Another broad category of cell modeling and SoC determination technique involves measuring cell impedances over wide ranges of AC frequencies at different states of charge. Values of the model parameters are found by taking least squares of measured impedance values. This method is not suitable for our application because it needs to inject signals directly into the cell to measure its impedances [6,8].

Other reported methods for estimating SoC have been based on artificial neural networks [9] and fuzzy logic [10] principles, although the latter was reported to have relatively poor performance. Although such techniques cause large computation overhead on the battery pack controller, which previously caused problems for online implementa-

tion, the increasing computational power of digital signal processing chips and the accompanying reduction in device costs may, in the near future, make their application an attractive alternative. Neural networks, in particular, have been used to avoid the need of the large number of empirically derived parameters required by other methods.

Indeed, for portable equipment application, where the task of prediction of SoC is less demanding, a neural network modeling approach has been shown to give mean errors of 3% [11]. Also, a neural network model for predicting battery power capacity during driving cycles has been added to the ADVISOR EV and HEV modeling environments [1].

Here then, model based state estimation techniques are proposed to predict the states of a cell that are normally difficult or expensive to measure or are subjected to the significant problems described previously. In this case, the SoC is the key state. Using an error correction mechanism, the observers provide real-time predictions of SoC. Specifically, the well known extended Kalman filter (EKF), developed during the 1960s to provide a recursive solution to optimal linear filtering for both state observation and prediction problems [12], is used for this study; a unique feature of the EKF is that it optimally (minimum variance) estimates states affected by broadband noise contained within the system bandwidth, i.e. that cannot otherwise be filtered out using classical techniques, and enables empirical tradeoffs between modeling errors and the influence of noise. A KF based method has been used in Ref. [2] with a linear state space battery model for SoC estimation, whereas in this paper, we have employed the EKF due to the nonlinear nature of the battery.

2. Battery model

A dynamic model of the battery, in the form of state variable equations, is necessary to predict the SoC. Here, a generic model [13,14] consisting of a bulk capacitor C_{bulk} to characterize the ability of the battery to store charge, a capacitor to model surface capacitance and diffusion effects within the cell C_{surface} , a terminal resistance R_t , surface resistance R_s and end resistance R_e , is employed as shown by Fig. 2. The voltage across the bulk and surface capacitors are denoted V_{cb} and V_{cs} , respectively. In this model,

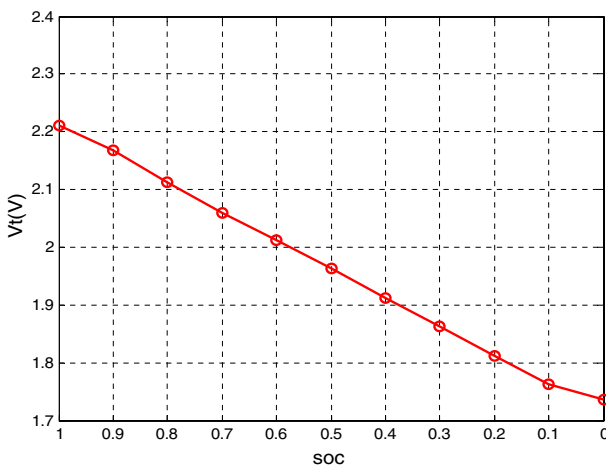


Fig. 1. Open circuit voltage versus SoC.

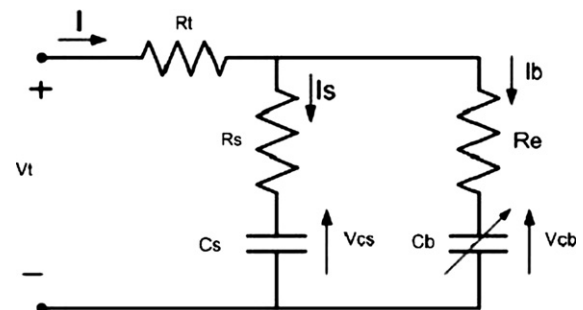


Fig. 2. RC battery model.

battery current is positive for the charging mode and negative for the discharging mode.

The initial parameters of the cell are calculated from experimental data where open circuit voltage (OCV) tests were performed upon successive discharges of the battery by application of current pulses. An initial estimate of C_{bulk} is obtained by analyzing the amount of stored energy in the cell, while the provisional value of C_{surface} relies on calculating the time constant of the cell in response to high frequency excitation. Complete derivation details, along with the initial parameters for the cells considered, are given in the following section for completeness.

3. Calculation of initial parameters

The initial parameters required for the battery model are determined from experimental data. In this paper, we have used a 6 Ah, 2 V sealed lead-acid cell manufactured by the SABA Battery Co. Iran, where OCV tests are performed upon successive discharges of the battery by injection of current pulses.

3.1. Capacitor C_{bulk}

The capacitance is determined by analyzing the amount of stored energy. Fig. 3 shows the OCV when discharge current pulses of 1.53 A are applied for 3600 s at 5400 s intervals [2]. The energy stored in C_{bulk} is determined from the OCV at 0% SOC and 100% SOC, using the following expression:

$$E_{C_{\text{bulk}}} = \frac{1}{2} C_{\text{bulk}} V^2 = \frac{1}{2} C_{\text{bulk}} (V_{100\% \text{ SOC}}^2 - V_{0\% \text{ SOC}}^2) \quad (1)$$

$E_{C_{\text{bulk}}}$ is equivalent to the rated Amp-sec capacity of the battery, giving:

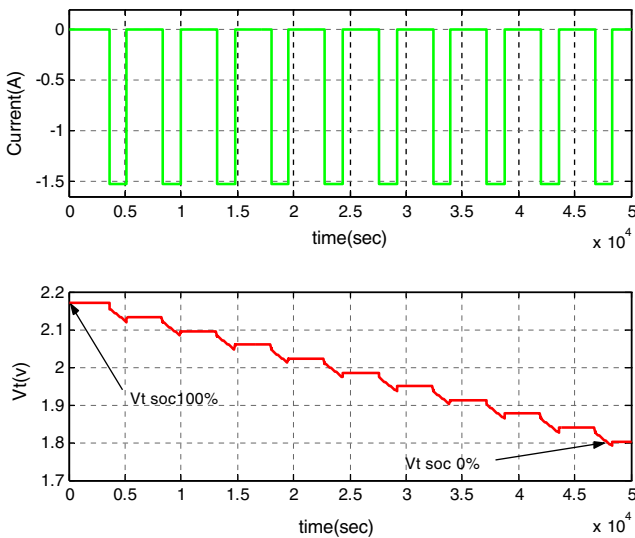


Fig. 3. Cell terminal voltage when discharge current pulses of 1.53 A are applied.

$$C_{\text{bulk-initial}} = \frac{\text{Rated(Amp-sec)} * V_{100\% \text{ SOC}}}{\frac{1}{2} (V_{100\% \text{ SOC}}^2 - V_{0\% \text{ SOC}}^2)} \quad (2)$$

$V_{100\% \text{ SOC}}$ and $V_{0\% \text{ SOC}}$ have been presented in Fig. 3.

3.2. Capacitor C_{surface}

The initial value of C_{surface} relies on the results of high frequency excitation of the cell to determine the time constant given by the surface capacitor and its associated resistance. As before, OCV tests are performed. Discharge pulses of 10 A are applied at 500 ms intervals, thereby isolating the results from the effects of C_{bulk} . From Fig. 4, it is seen that

$$V_1 = 2.168, \quad V_2 = 2.102$$

$$V_3 = 2.157, \quad V_4 = 2.1645$$

$$\Delta t = 0.5 \text{ s}$$

The time constant is approximated using the following relationship:

$$V_{\text{no-load}} = V_1 = V_3 + (V_4 - V_3)(I - e^{\frac{-t}{\tau}}) \quad (3)$$

and solving for τ gives:

$$\tau = -\Delta t \ln \left(1 - \frac{V_4 - V_3}{V_1 - V_3} \right) = 0.58 \text{ s} \quad (4)$$

The time constant is described by

$$\tau = (R_s + R_e) C_{\text{surface}} \quad (5)$$

Hence, the initial estimate of the surface capacitor is determined as

$$C_{\text{surface-initial}} = \frac{\tau}{R_e + R_s} \quad (6)$$

3.3. Battery resistance

The internal resistance of the battery is measured as 5.6 m Ω . It is assumed that R_s and R_e are equivalent and account for 80% of the total resistance. Hence, R_t is

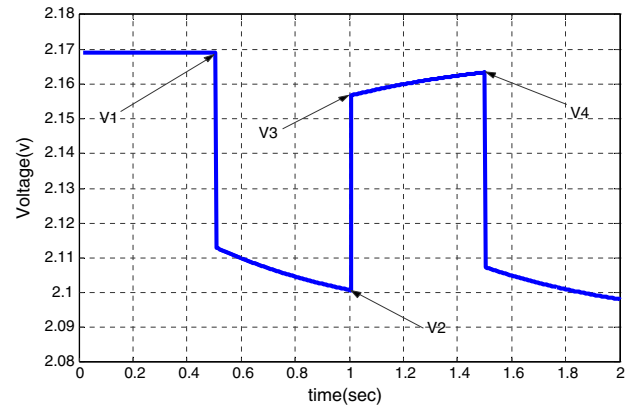


Fig. 4. Cell terminal voltage when a discharge current of 10 A pulse is applied at 500 ms intervals.

Table 1
Initial parameter for cell model

Parameters	C_{bulk} (F)	C_{surface} (F)	R_e (Ω)	R_s (Ω)	R_t (Ω)
Value	66092	66092	0.00448	0.00448	0.00336

$$0.0056 = R_t + \left[\frac{1}{R_e} + \frac{1}{R_s} \right] \quad (7)$$

A summary of initial values is given in Table 1.

4. State variable description of battery model

4.1. State variables V_{cb} , V_{cs} , V_t and α

Voltages and currents describing the characteristics of the network shown in Fig. 2 are given by (note: by convention, current flowing into the cell is considered positive and $\alpha = 1/C_{\text{bulk}}$)

$$V_t = IR_t + I_b R_e + V_{cb} \quad (8)$$

$$V_t = IR_t + I_s R_s + V_{cs} \quad (9)$$

where I , I_s and I_b are battery terminal current, C_{surface} current and C_{bulk} current, respectively. For simplicity, assume that $R_s = R_e$. Equating the two voltage Eqs. (8) and (9) yields:

$$I_b R_e = I_s R_e + V_{cs} - V_{cb} \quad (10)$$

By applying Kirchoff's laws, $I = I_s + I_b$ and Eq. (10):

$$2I_b R_e = IR_e + V_{cs} - V_{cb} \quad (11)$$

Since $I_b = \dot{V}_{cb}/\alpha$, Eq. (11) can be rearranged to give

$$\dot{V}_{cb} = -\frac{\alpha \times V_{cb}}{2R_e} + \frac{\alpha \times V_{cs}}{2R_e} + \frac{\alpha \times I}{2} \quad (12)$$

where $\alpha = 1/C_{\text{bulk}}$.

Through a similar derivation, the rate of change of the surface capacitor voltage is obtained from Eqs. (8) and (9) as

$$\dot{V}_{cs} = -\frac{V_{cs}}{2C_{\text{surface}}R_e} + \frac{V_{cb}}{2C_{\text{surface}}R_e} + \frac{I}{2C_{\text{surface}}} \quad (13)$$

and the output voltage, as a function of terminal current, is given from Eqs. (8) and (9) by

$$V_t = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} V_{cb} \\ V_{cs} \end{bmatrix} + \begin{bmatrix} R_t & \frac{R_e}{2} \end{bmatrix} I \quad (14)$$

Taking the time derivative of the output voltage and assuming $dI/dt \approx 0$ (the rate of change of terminal current per sampling interval when implemented digitally is negligible) gives

$$\begin{aligned} \dot{V}_t = & \left[-\frac{\alpha}{2R_e} + \frac{1}{2C_{\text{surface}}R_e} \right] V_{cb} \\ & + \left[\frac{\alpha}{2R_e} - \frac{1}{2C_{\text{surface}}R_e} \right] V_{cs} \\ & + \left[\frac{1}{2C_{\text{surface}}} - \frac{R_t \times \alpha}{2R_e} + \frac{R_t}{2R_e C_{\text{surface}}} \right] I \end{aligned} \quad (15)$$

Here, we have added an extra state $\alpha = 1/C_{\text{bulk}}$ into the model state space and assumed the rate of change of C_{bulk} over a sampling interval is negligible, e.g. $d\alpha/dt = 0$. Solving Eq. (14) and substituting into Eq. (15) provides a complete state variable description of the network as

$$\begin{aligned} \dot{x} &= f(x, u) \\ y &= C(x) \end{aligned} \quad (16)$$

In this nonlinear state space, we have

$$x = [V_{cb} \quad V_{cs} \quad V_t \quad \alpha]^T \quad (17)$$

and

$$C(x) = V_t, \quad u = I \quad (18)$$

$$f(x, u) = [f_1 \quad f_2 \quad f_3 \quad f_4]^T \quad (19)$$

that

$$\begin{aligned} f_1 &= -\frac{x_4 \times x_1}{2R_e} + \frac{x_4 \times x_2}{2R_e} + \frac{x_4 \times I}{2} \\ f_2 &= -\frac{x_2}{2C_{\text{surface}}R_e} + \frac{x_1}{2C_{\text{surface}}R_e} + \frac{I}{2C_{\text{surface}}} \\ f_3 &= \left[-\frac{x_4}{2R_e} + \frac{1}{2C_{\text{surface}}R_e} \right] x_1 \\ &\quad + \left[\frac{x_4}{2R_e} - \frac{1}{2C_{\text{surface}}R_e} \right] x_2 \\ &\quad + \left[\frac{1}{2C_{\text{surface}}} - \frac{R_t \times x_4}{2R_e} + \frac{R_t}{2R_e C_{\text{surface}}} \right] I \\ f_4 &= 0 \end{aligned} \quad (20)$$

4.2. Observability of the RC battery model

Observability of the system must be investigated after system linearization. Calculating the observability matrix shows that this matrix is always of full rank under mild conditions.

4.3. Formulation of EKF for SoC estimation

Since the derivatives of V_{cb} , V_{cs} and V_t are coupled by nonlinear elements, noting that the derivative of α is equal to zero, the EKF is now required for effective estimation of the state variables. The proposed nonlinear battery model is written in the form of:

$$\begin{aligned} \dot{x} &= f(x, u) \\ y &= C(x) \end{aligned}$$

The EKF requires a small signal model of the system at each sample step. By linearizing Eq. (20) about the current operating point x_0 , u_0 and using the Jacobian matrix, we obtain a linear system.

$$\begin{aligned} \delta \dot{x} &= A_k \delta x + B_k \delta u \\ \delta y &= C_k \delta x \end{aligned} \quad (21)$$

where

$$\begin{aligned}
A_k &= \left. \frac{df(x, u)}{dx} \right|_{x_k, u_k} \\
B_k &= \left. \frac{df(x, u)}{du} \right|_{x_k, u_k} \\
C_k &= \left. \frac{dC(x)}{dx} \right|_{x_k, u_k} = C
\end{aligned} \quad (22)$$

Now, we calculate these matrices for our system:

$$\begin{aligned}
A_k &= \begin{bmatrix} a_{11} & a_{12} & 0 & a_{14} \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & 0 & a_{33} & a_{34} \\ 0 & 0 & 0 & 0 \end{bmatrix} \\
a_{11} &= -a_{12} = -\frac{x_{4k}}{2R_e}, \quad a_{14} = \frac{-x_{1k} + x_{2k} + I_k R_e}{2R_e} \\
a_{21} &= -a_{22} = \frac{1}{2R_e C_{\text{surface}}}, \quad a_{31} = -\frac{x_{4k}}{2R_e} + \frac{1}{2R_e C_{\text{surface}}} \\
a_{33} &= \frac{x_{4k}}{2R_e} - \frac{1}{2R_e C_{\text{surface}}}, \quad a_{34} = -\frac{x_{1k}}{2R_e} + \frac{x_{3k}}{2R_e} - \frac{I_k R_t}{2R_e}
\end{aligned} \quad (23)$$

and

$$\begin{aligned}
B_k &= \begin{bmatrix} \frac{x_{4k}}{2} & \frac{1}{2C_{\text{surface}}} & b_{13} & 0 \end{bmatrix}^T \\
b_{13} &= \frac{1}{2C_{\text{surface}}} - \frac{R_t x_{4k}}{2R_e} + \frac{R_t}{2R_e C_{\text{surface}}}
\end{aligned} \quad (24)$$

ultimately,

$$C = \begin{bmatrix} 0 & 0 & 1 & 0 \end{bmatrix} \quad (25)$$

Assuming the applied input u is constant during each sampling interval, a discrete time equivalent model of the system is given by:

$$\begin{aligned}
x_{k+1} &= A_d x_k + B_d u_k \\
y_{k+1} &= H x_{k+1}
\end{aligned} \quad (26)$$

where

$$\begin{aligned}
A_{dk} &\approx I + A_k \Delta T, \quad B_{dk} = B_k \Delta T \\
H &= C
\end{aligned} \quad (27)$$

and ΔT is the sampling period. The system is now assumed to be corrupted by stationary Gaussian white noise via the additive vectors σ_k and μ_k . The former vector is used to represent system disturbances and model inaccuracies, and the latter represents the effects of measurement noise. Both σ_k and μ_k are considered to have a zero mean value, for all k , with the following covariance matrices (E denoting the expectation operator):

$$\begin{aligned}
E[\sigma_k \sigma_k^T] &= Q \quad \text{for all } k \\
E[\mu_k \mu_k^T] &= R \quad \text{for all } k
\end{aligned} \quad (28)$$

The resulting system is, therefore, described by

$$\begin{aligned}
x_{k+1} &= A_{dk} x_k + B_{dk} u_k + \sigma_k \\
z_{k+1} &= H x_{k+1} + \mu_{k+1}
\end{aligned} \quad (29)$$

where z is the vector of measured outputs after being corrupted by noise.

For notational purposes, we define $\hat{x}_k^-$ (note the “super minus”) to be our *a priori* state estimate at step k given knowledge of the process prior to step k , and $\hat{x}_k$ to be our *a posteriori* state estimate at step k given measurement z_k . We can then define *a priori* and *a posteriori* estimate errors as

$$\begin{aligned}
e_k^- &= x_k - \hat{x}_k^- \\
e_k &= x_k - \hat{x}_k
\end{aligned} \quad (30)$$

The *a priori* estimate error covariance and *posteriori* estimate error covariance are then

$$P_k^- = E[e_k^- e_k^{-T}], \quad P_k = E[e_k e_k^T] \quad (31)$$

A property of the EKF is that the estimated state vector $\hat{x}_k$ of the system, at time k , minimizes the sum of squared errors between the actual and estimated states.

$$\min\{P_k\} = \min\{E[(x_k - \hat{x}_k)(x_k - \hat{x}_k)^T]\} \quad (32)$$

For recursive implementation, the EKF estimate $\hat{x}_{k+1}$ is calculated from the previous state estimate $\hat{x}_k$, the input u and

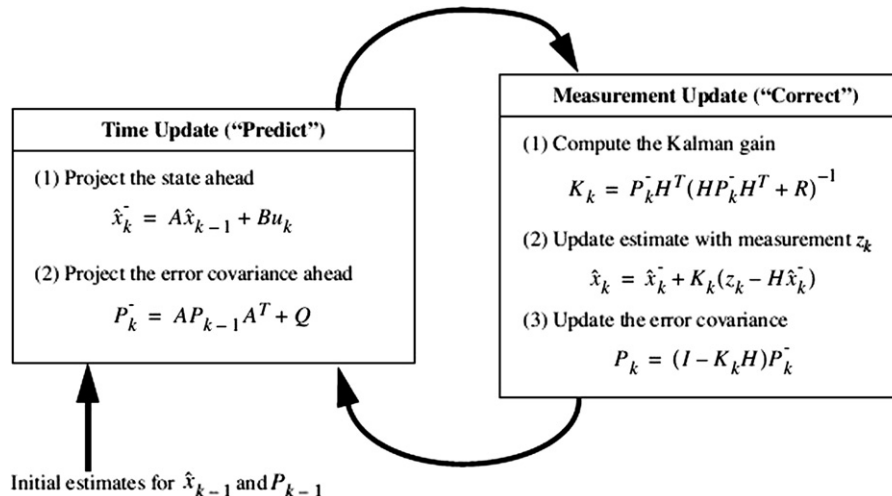


Fig. 5. Recursive EKF algorithm.

the measurement signals z . The available input/output data at each sample step is, therefore, considered to be $u_0, u_1, u_2 \dots u_k, u_{k+1}$ and $z_0, z_1, z_2 \dots z_k, z_{k+1}$. The recursive EKF algorithm is obtained with the predictor/corrector stages being explicitly identified in Fig. 5 [12].

5. Implementation of EKF

The stochastic principles underpinning the EKF are appealing for this investigation, since it is recognized that the presence of disturbances stemming from sensor noise on the cell terminal measurements and the use of non-ideal dynamic models make it impossible to predict the states of the system over prolonged time periods with certainty. A statistical predictor/corrector formulation thereby provides obvious advantages.

Since only terminal quantities of the battery can be measured, the input is defined as $u = I$ and the measured output is $y = V_t$. Although no formal stability and tuning methods are available for initializing the EKF and recourse to empirical tuning is normally required, its use

is nevertheless widespread. Information about the system noise contribution is contained in matrices Q and R and, in essence, the selection of Q and R determines the accuracy of the filter's performance, since they mutually determine the action of the EKF gain matrix K_{k+1} and estimation error covariance matrix P_{k+1} . The covariance matrix representing measurement noise R can be estimated from knowledge of the battery terminal voltage. The variance is obtained from the square of the root mean square (rms) of noise on each cell and is assumed to be Gaussian distributed and independent.

Initialization of the covariance matrix describing the disturbances on the plant Q is complicated while knowledge of the model inaccuracies and system disturbances is limited, particularly as each cell has different characteristics [12]. A judicious choice of Q is, therefore, obtained from experimental studies under the simplifying assumption that there is no correlation between the elements of σ_k and the noise present on each cell's voltage transducer, thereby leading to a diagonal Q . The initial covariance matrix P_0 together with Q and R , for our case, are ultimately chosen to be:

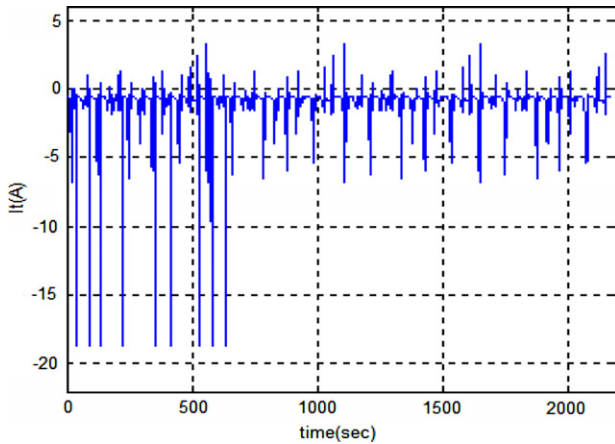


Fig. 6. Manhattan driving cycle current.

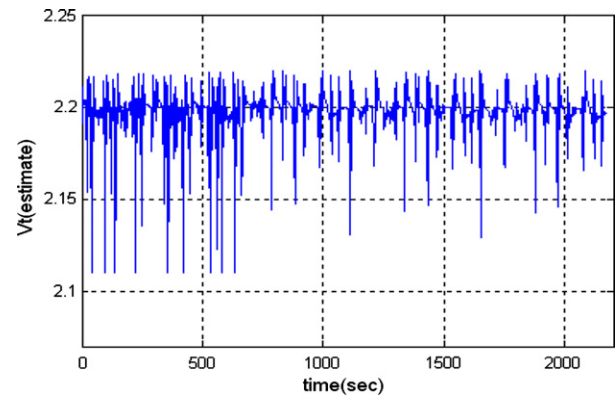


Fig. 8. Estimated terminal voltage.

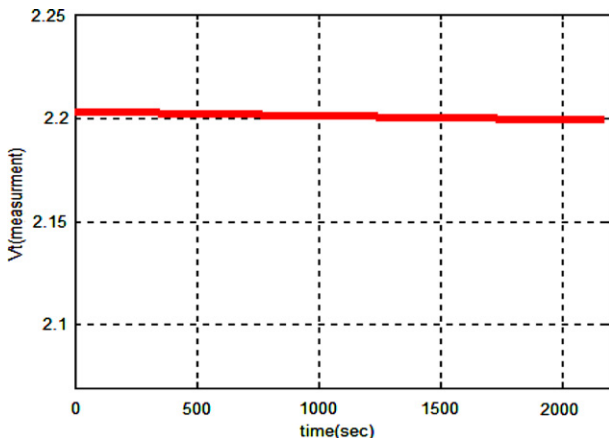


Fig. 7. Measurement terminal voltage.

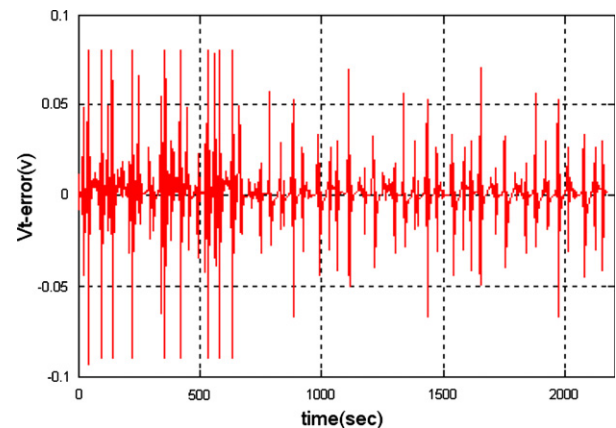


Fig. 9. Terminal voltage error.

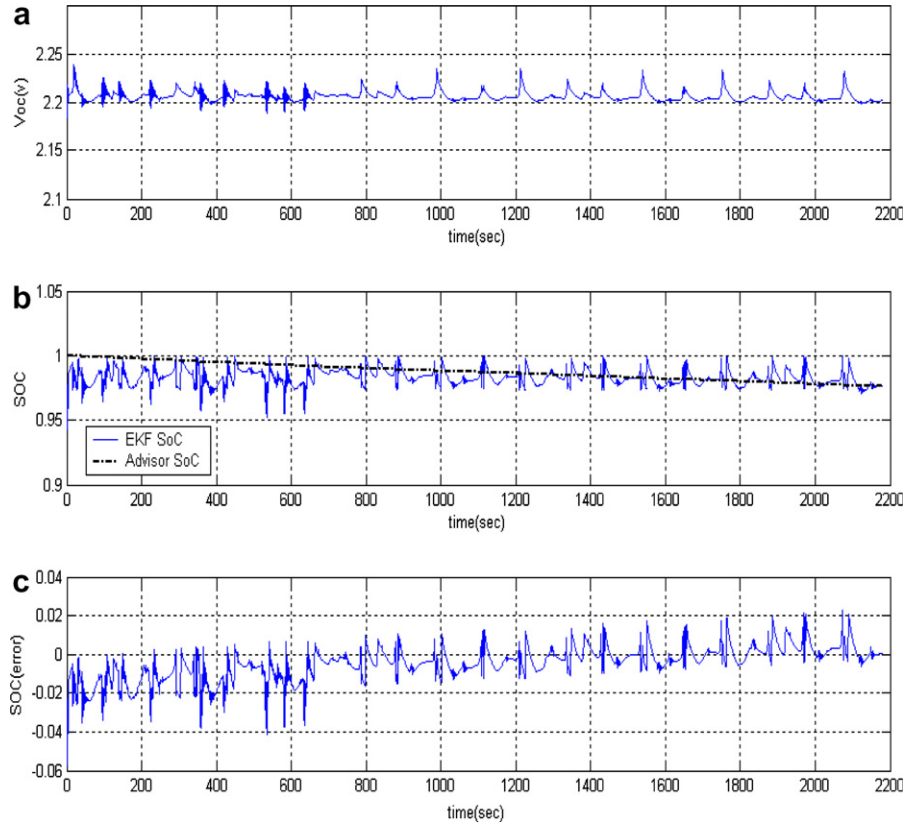


Fig. 10. (a) Open circuit voltage (V_{cb}). (b) EKF SoC and Advisor SoC. (c) Difference between EKF SoC and Advisor SoC.

$$P_0 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad R = 10 \quad (33)$$

$$Q = \begin{bmatrix} 0.005 & 0 & 0 & 0 \\ 0 & 0.07 & 0 & 0 \\ 0 & 0 & 0.9 & 0 \\ 0 & 0 & 0 & 0.0001 \end{bmatrix}$$

6. Simulation results

The EKF was applied to the real-time estimation of the SoC of a single cell that was subjected to a Manhattan driving cycle [1]. Fig. 6 shows the cell terminal current for this driving cycle. The initial cell SoC was set to 1.0. Note that $\text{SoC} = 1$ is a normalized value used to define a fully charged cell. The measured and estimated terminal voltages for the Manhattan driving cycle are illustrated in Figs. 7 and 8, respectively, and their errors are shown in Fig. 9.

Fig. 9 shows that the maximum terminal voltage error is less than 0.1 V, i.e. less than 4%. Ultimately, we show the results of the SoC and open circuit voltage (V_{cb}) estimation by the EKF and compare these results with the Advisor SoC estimation (R_{int} based method) in Fig. 10.

7. Conclusion

This paper presented an alternative approach to estimate the SoC of a cell pack by the application of an EKF. It was shown that when using a generic model to describe the dynamic behavior of lead-acid cells, large state errors can develop over time. In particular, a comparison between SoC estimation based on the EKF technique and the more conventional methods based on internal resistance (that was used in Advisor for indication of the SoC for the Toyota Prius HEV) shows 3% difference in results. We do not use the word ‘error’ because R_{int} based methods are static and are not suitable for modeling dynamic systems, therefore we can not use it as a reference method. This method is only used for comparison of the static method against the dynamic method. The results demonstrate that the proposed technique and new battery model are very suitable for presentation of the battery’s dynamic behavior and indication of the battery’s SoC.

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